Learning Object Tendency:  
A New Concept for Adaptive Learning Improvement

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Abstract

Improving the learning quality in e-learning environments has received considerable attention from researchers. One of the methods to improve the understanding of the students in a learning process is adapting the content to their learning styles. The learning style models are used to classify the students in different groups based on their appropriate style of learning. In e-learning we can use the learning styles to categorize learning contents suitable for each group. In this paper we present a new concept called Learning Object Tendency. Considering this concept the learning objects are classified based on the learning styles of the students. Therefore, by determining the tendency of a learning object, we can present that the appropriate learning object to the learners. To determine the tendency of a learning object we proposed a method based on the assessment of the learner progress in a learning object. The Felder-Silverman Learning Style Model is used to determine the learning style of the students. The pre-tests and post-tests are taken before and after presentation of each learning object to estimate the level of learning progress. By applying the results of the tests to a probabilistic model we classify the learning object in a specific tendency.

Keywords: Learning Object Tendency, Felder-Silverman Learning Style Model, Probabilistic Learner Knowledge Model, Adaptive E-Learning.

1. Introduction

In virtual learning environments, one of the main purposes is to minimize the involvement of teachers during the learning process, while keeping the advantages of the real classes in new systems.

Today, web-based virtual learning is not just presenting the learning content to learners by means of the web. The new Intelligent Tutoring Systems (ITS) provide intelligent adaptivity for their users. The aim of ITS is to improve the learning process of the students without any human intervention.

Learning style is an important issue in the pedagogical physiology. This issue has received attention from Learning Management System (LMS) developers (Mayo and Mitrovic, 2001; Karagiannidis and Sampson, 2002; Dagger et al, 2002; Arroyo et al., 2004).
In this paper, we defined the “Learning Tendency” of learning Objects concept that can be used to enhance the learning process of learners by presenting the most appropriate learning object to them based on their learning style.

High quality learning materials are expensive to create. So it is very important to ensure reuse of learning content. Reuse is made possible by annotating learning content with metadata. Manual annotation is a time consuming and expensive process. It is also liable to human errors (Roy, 2006). One of the important possible metadata for learning content is the “Learning Tendency” introduced in this paper.

The rest of this paper is organized as follows. In section 2, we will present an overview of the learning style models and their usage in virtual learning. Section 3 describes the structure used for scaffolding of the learning content and making a hierarchical structure based on learning objectives, and composed of learning objects. In the section 4, we describe the assessment methods, and the Bayesian network model that we used for estimation of the learner’s knowledge. In the section 5, the main process of determination of the Learning Object Tendency and the proposed Bayesian model used for it, is explained. The section 6 demonstrates the related works in the literature. Finally, in the section 7 the conclusion and future works is presented.

2. Learning Style Model

Different adaptations have been applied in different systems. One of the methods to improve the understanding of the students in a learning process is adapting the content to their learning styles. The learning style models are used to classify the students in different groups based on their appropriate style of learning. The learning style of a student determines what type of information he prefers, what channels he desire for perceiving the new information, how a student processes new information and how does he progress toward understanding.

2.1. Usage of Learning Styles in Virtual Learning

There are many different learning style models proposed for different usages. For a list of more important learning style models, you can refer to (Karagiannidis and Sampson, 2002). Since the population under study are engineering students, we used Felder-Silverman Learning Style Model in this research. In the following section, we will have a closer look at this model.

2.2. Felder-Silverman Learning Style Model

This model was proposed in 1988 by Felder and Silverman (Felder, Silverman, 1988) for engineering students. Since then it has been used by researchers in the e-learning field (e.g. Graf and Kinshuk, 2006; Liu et al., 2007; Sun et al., 2007). It has been revised on
2002 by Felder. We used the revised version that has four dimensions. These dimensions are Sensory/Intuitive, Visual/Verbal, Active/Reflective and Sequential/Global. They address the preferred knowledge perception, data input, processing and understanding for the learner respectively (Felder, Silverman, 1988).

2.3. Normalization of the Learning Style Data

The proposed tool for determining the students learning style in this model is a questionnaire called Index of Learning styles (ILS) (Felder, Soloman, 1996). To help the students in answering this questionnaire we provided a translated version of the questionnaire, and presented to them.

The ILS results are four numbers ranging from – 11 to 11 for each dimension. We mapped these results to the range of 0-1 by the equation [1] where \(i\) is the ILS result for a dimension and \(ns\) is the normalized style value.

\[
ns = \frac{i + 11}{22}
\]

3. Learning Objectives and Learning Objects

Learning content scaffolding helps creating more adaptable and reusable learning contents. Assigning a particular structure to a learning content needs some pedagogical knowledge; this introduces the interdisciplinary research between information technology experts and learning psychologists.

For knowledge assessment, researchers used different knowledge structures. The Knowledge Space Theory was used by the Knowledge and Data Engineering Group of Trinity College in their works (Conlan et al., 2006). Collins used Granularity Hierarchies, which had been used with Bayesian belief network for Computer Adapted Testing (Collins et al., 1996); in this Granularity Hierarchies, the concepts and skills are aggregated to form levels of details.

In our research, we used the learning objective hierarchy. In this hierarchy, a learning objective is assigned to each Learning Object. Each learning objective consists of 1 to 3 skills. A set of questions is assigned to each skill. A question may require up to three skills. This hierarchy is very similar to the Bayesian model shown in Figure 1.

4. Estimating learner’s progress

Determination of the “Learning Object Tendency” introduced in this paper, is based on learner’s progress during the usage of a specific learning object. This progress is evaluated by learner assessment before and after taking the content related to a specific learning object (Pre-test and Post-test). Therefore, we need to accomplish a precise
knowledge assessment for each user. In this section, we will discuss the problems in this process and the solution using Bayesian networks.

4.1. Learner’s Knowledge Estimation Problems

There are two common problems in assessments, when explicit tests are being used to determine the knowledge of learners. These problems have been addressed before e.g. (Conati et al., 2002; Pardos et al., 2006).

4.1.1. Credit-Blame Problem

This problem happens when a learner answers a question with more than one objective being assigned to it. If the answer is not correct then, normally the blame goes to all the skills needed for that question. Let us consider a question Q1 with two objectives (OB1 and OB2). Prior to this question learner has answered three questions related to OB1 and all of them are answered correctly; conversely she only answered one of the four questions related to OB2 correctly. According to the conventional scoring system, the blame will be divided equally between the OB1 and OB2 and the result will be:

\[
\frac{3}{3.5} = 86\% \rightarrow \text{OB1} \quad \text{and} \quad \frac{1}{4.5} = 22\% \rightarrow \text{OB2}
\]

However, considering the prior scores of the OB1 and OB2, it is more likely that the learner lacked the skill of OB2 when answering this question, so the more blame must be assigned to OB2.

Prior Scores:

\[
\begin{align*}
100\% \rightarrow & \text{OB1} \\
25\% \rightarrow & \text{OB2}
\end{align*}
\]

\[
\Rightarrow \begin{cases} 
\text{Blame(OB1)} = (25/125) = 0.2 \\
\text{Blame(OB2)} = (100/125) = 0.8
\end{cases}
\]

With this approach the scores will adjusted as follows:

\[
\frac{3}{3.2} = 94\% \rightarrow \text{OB1} \quad \text{and} \quad \frac{1}{4.8} = 21\% \rightarrow \text{OB2}
\]

4.1.2. Guess-Slip Problem

When a learner is faced to a test question, he/she may either have the required knowledge for it or not. However, having the knowledge does not necessarily lead to correct answer. On the other hand, if the question is multiple-choice he/she may give a correct answer to a question by chance without having the required knowledge.
4.2. Using Bayesian Networks to Deal With the Problems

In general, Bayesian network models have been used for assessment since mid 90s (Martin and Vanlehn, 1995; Conati et al., 1996; Vanlehn and Martin, 1997; Conati et al., 2002; Pardos et al., 2006). The Bayesian belief network was used for estimating the student mastery in Computer Adapted Testing (CAT) as well (Collins et al., 1996; Linacre, 2000; Desmarais and Pu, 2005).

The Bayesian networks have been used to address Credit-Blame in (Conati et al., 2002). In (Pardos et al, 2006) the authors assigned a fixed chance for Guess and Slip in answering the questions and used a Bayesian model to handle the Guess-Slip Problem.

4.2.1. Prior Probabilities

Different methods have been used to assign prior probability to nodes in the Bayesian network model. For example, the average of former students is used as an initiating value for the model of each new student in PKOS (Desmarais and Pu, 2005). In a CAT algorithm suggested by Halkitis, an initial value for the ability estimate is provided by an initialization mechanism. In this mechanism, each student is awarded one success and one failure on two dummy questions (Linacre, 2000).

In this work, to calculate the prior probabilities we used a set of tests specifically designed so that it requires just one skill to solve. These tests were provided to learners as pre-tests. The scores of the tests for each skill was calculated and then mapped to a range of 0-1. This value is assigned to the designated node for that skill in the model.

4.2.2. The Proposed Model and Methods

In order to estimate the learner’s knowledge of each Learning Objective, a Bayesian network model as shown in Figure 1 is used. In this model, the leaf nodes represent the questions designed for this Learning Object. To handle the credit-blame problem, the following strategy was used:

- For the correct answers, the credit is dispatched between the parent nodes (skills) relative to their current mastery probability.
- For each wrong answer, the blame is dispatched between the parent nodes in reverse proportion of their current mastery probability (section 4.1.1).
For the guess-slip problem, instead of a fixed guess probability for the multiple-choice questions (e.g. 0.25 for tests with 4 choices), a new approach was used. In this approach, the prior probability of the parent node is also considered in calculating the guess chance. Three levels for the prior probability of the parent node were defined (less than 0.5, between 0.5 and 0.8 and above 0.8). In the first level, the knowledge of the learner is considered very low, so the basic guess chance is doubled. In the second level, the learner’s knowledge is considered low, and the basic guess chance is multiplied by 1.5. Finally, in the third level the basic guess chance is used. If the question node (Q) has more than one parent (e.g. P1 and P2), then equation [2] is applied to calculate the conditional probability of Q, and this conditional probability is used in the levelling system.

\[ p(Q = True \mid P1 = True, P2 = True) = P1 \times P2 \]

To adjust the slip chance, a similar levelling system is used, but this time the values are less than 0.7, between 0.7 and 0.9 and above 0.9. In accordance, the slip chances of 0.05 for the first level, 0.1 for the second level and 0.2 for the third level are used. The guess and slip chances are used in the conditional probability tables of the question nodes. Table 1 shows the probability values of the question node “Question i”. It is a 5-choice question shown in the model presented in Figure 1. The values are related to the probability values of the node’s parents (S1 and S2). These values reflect the guess chance for a “correct” answer and slip chance for a “wrong” answer to this question.

Table 1

<table>
<thead>
<tr>
<th>Answer to the Question</th>
<th>Node value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct</td>
<td>( \text{if } (p(s1)\times p(s2))&gt;0.8 = 0.8 \text{ else if } (p(s1)\times p(s2))&gt;0.5 = 0.7 \text{ otherwise } = 0.6 )</td>
</tr>
<tr>
<td>Wrong</td>
<td>( \text{if } (p(s1)\times p(s2))&gt;0.9 = 0.2 \text{ else if } (p(s1)\times p(s2))&gt;0.5 = 0.1 \text{ otherwise } = 0.05 )</td>
</tr>
</tbody>
</table>
5. Determining the Learning Object Tendency

In order to determine the Learning Object Tendency for a particular Learning Object (LO), we compare learning progress of different learners in study of that LO, considering their learning style. To do so, first we take a pre-test to evaluate the prior knowledge of the learner for the learning objective related to this LO. Then we let the learner to study the LO through the LMS. When the learner thinks that he/she has understood the LO (and not before a determined time span, set in the LO itself) he/she will proceed to the post-tests. We used the method and the model described in section 4 to estimate the learner’s knowledge.

The next step is to calculate the progress of the learner. Here we used the difference between the prior knowledge estimate (calculated statically from the pre-tests) and the final value of knowledge estimate of the relevant Learning Objective, as the indicator for learner progress. In this work, we left out the negative progress, and we placed zero progress instead.

To utilize the progress data, we found the minimum and maximum of the progress data, and then we mapped this range to the range of 0-1. This progress data is used in the progress nodes in the proposed Bayesian model. The other leaf node-type is the learner’s learning style, normalized to the range of 0-1 (refer to section 2.3). After updating of the relevant nodes, the LO Tendency is estimated as four probability values which are further interpreted to form the LO Tendency. The proposed Bayesian model is shown in Figure 2. The tendency is determined based on the values according to the Table 2.

Figure 2. The Tendency Classification Model
6. Related Works

Automatic learning content labelling or classification is a new approach. A similar approach is taken by Roy et al., (Roy, 2006; Roy et al., 2007; Roy et al., 2008). They used natural language processing methods to annotate the learning content with some predefined metadata. Compared to it our method is also a feature extraction from learning content, but we use the experimental data for it.

7. Conclusion and Future Works

The tendency classification of learning objects can be used practically by labelling the learning objects with the assigned tendency values; this can be added to the learning content ontology or learning content models used in different Intelligent Learning Management Systems to enhance the effectiveness of adaptation and improve the learning process of the learners.

<table>
<thead>
<tr>
<th>The Tendency Classes</th>
<th>0-0.25</th>
<th>0.25-0.75</th>
<th>0.75-1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensory/Intuitive</td>
<td>Sensory</td>
<td>No preference</td>
<td>Intuitive</td>
</tr>
<tr>
<td>Visual/Verbal</td>
<td>Visual</td>
<td>No preference</td>
<td>Verbal</td>
</tr>
<tr>
<td>Active/Reflective</td>
<td>Active</td>
<td>No preference</td>
<td>Reflective</td>
</tr>
<tr>
<td>Sequential/Global</td>
<td>Sequential</td>
<td>No preference</td>
<td>Global</td>
</tr>
</tbody>
</table>

The Learning Object Tendency defined here can be thought as a metadata, which makes the adaptation to learning style of learners achievable, and subsequently improves the learning progress of the learners.

There is an undergoing research project done in the Advanced E-Learning Technologies Lab in Amirkabir University which utilizes the methods presented here to determine the LO Tendency for a set of contents. Another aim of this project is the utilization of the Tendency in learning content adaptation and observation of its positive effects in the learning progress of a virtual course.
REFERENCES


